

# Report on *Visualization and exploration of Adult Dataset*

CS245, Data Science Foundation, Chaojun Lu, Autumn 2017

## 1 Introduction

Currently, data science is becoming ubiquitous in our society and showing its essentiality in many domains (e.g. medical industry [1, 2], finance [3], social media [4, 5]). With the rapid evolution and wide applications of data science, a series of efficient packages have been constantly developed [6, 7, 8, 9]. Utilizing these packages skillfully is of great importance nowadays. In this project, I tend to conduct some explorations over the *Adult* dataset and visualize the results with some of these packages.

## 2 Approaches

The *Adult* dataset is in the format of .CSV with 16281 lines, each line contains some basic information (age, job, gender and etc) of an adult. I explore and extract the information hidden in the data with the following steps:

1. Read the data with *pandas* [7] and reconstruct it as a *DataFrame* type variable.
2. Select a target attribute (e.g. work time per week) to carry out some analyses.
3. Select two attributes to explore the implicit relations between them.
4. Visualize all analyses results with *matplotlib* [8] and *pandas*.

## 3 Experiments

### 3.1 Experiments Setup

Since the data is organized as .CSV format, it is easy to be recognized by *pandas*. I first construct the dataset as a *DataFrame* with 16281 lines and 15 columns, each line denotes the information of an adult while each column represents an attribute.

### 3.2 The Distribution of Single Attribute

Basically, it is of great significance to figure out the distribution of some attributes in the data. I hence explore some of them and visualize the results with corresponding figure types \*.

1. The distribution of **educational background** in the dataset is shown in Fig. 1(a).

The result shows the educational background of many adults are high school or college, occupying more than half of the proportion. Only a few people owns bad educational background (e.g. preschool).

2. In the meantime, I also plot the distribution of **schooling years** in Fig. 1(b).

Indeed, the schooling years are extremely related to educational background, the two distributions are hence quite similar.

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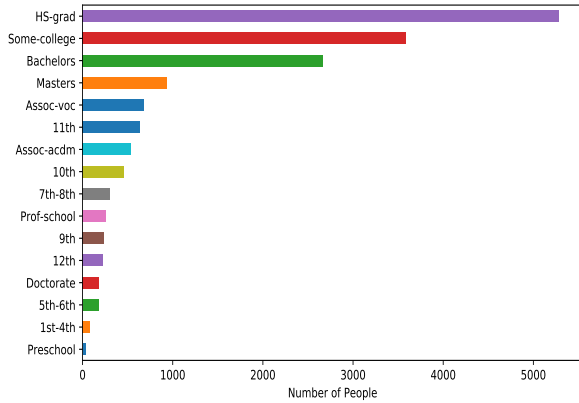
\*More figures can refer to Appendix A

3. The distribution of **family relations** can refer to Fig. 1(c).

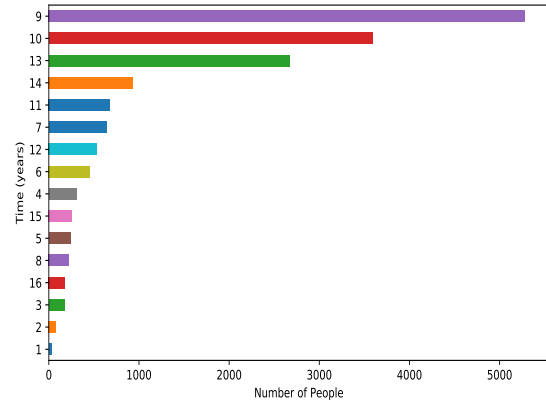
The result indicates more than half of the adults have set up a family, while there still exist many adults remain unmarried or not in family, which surprises me a little.

4. The distribution of **working time per week** can be found in Fig. 1(d).

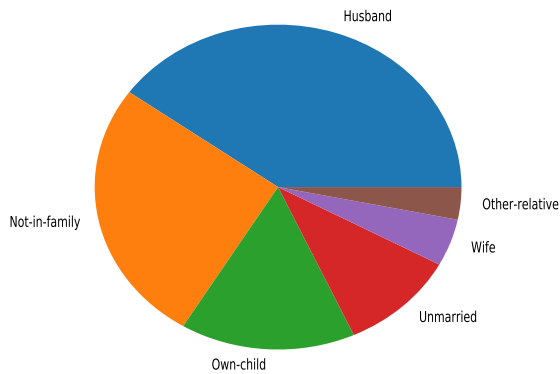
This Kernel Density Estimation(KDE) figure shows that most adults work about 40 hours per week, and a few people also work more than 60 hours per week. To find out more hidden information, I will conduct some deep explorations in Sec. 3.3.2 and Sec. 3.3.3.



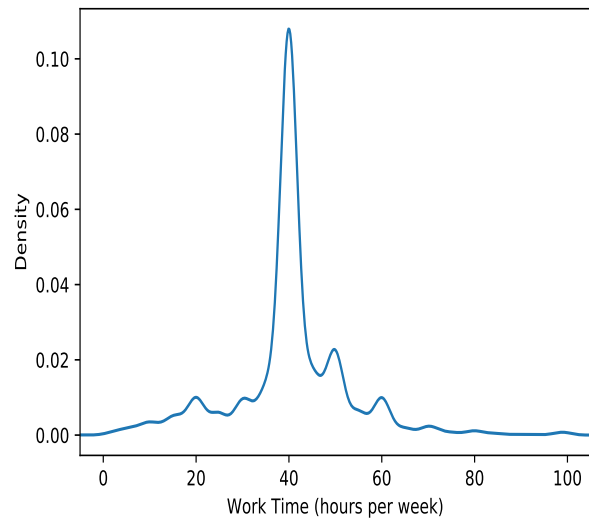
(a) Distribution of Educational Background



(b) Distribution of Schooling Years



(c) Distribution of Family Relations



(d) Distribution of Work Time

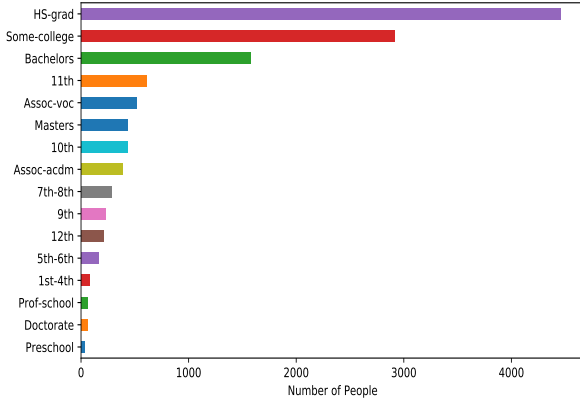
Figure 1: The Distribution of Some Single Attributes.

### 3.3 The Relation between Two Attributes

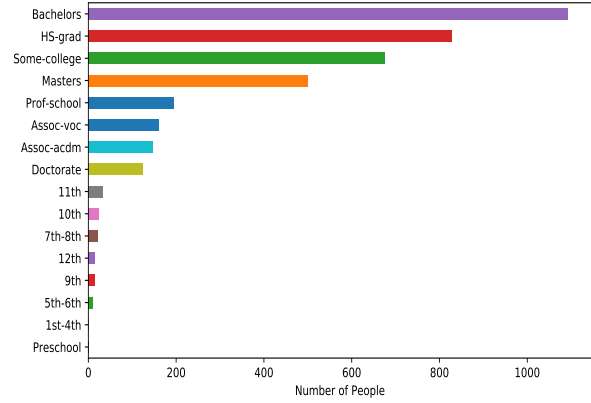
Generally speaking, it is not enough to extract only the distribution of single attribute. Therefore, in this section, I would explore some relations between two attributes.

### 3.3.1 Salary vs. Educational Background

I tend to start with the relation between salary and educational background. The salary in *Adult* dataset is divided into two catagories: *more than 50K* and *less or equal to 50K*. The following two bar figures (Fig. 2) represent the distribution of educational background under different salary conditions.



(a) Salary is less or equal to 50K



(b) Salary is more than 50K

Figure 2: The distribution of educational background under different salaries.

One of the main points implied by the two distributions is that higher education brings higher salary, which conforms to common sense. Nevertheless, there also exist some people enjoying high salary with low educational background, which illustrates that educational background can not completely determine a person.

### 3.3.2 Work Time vs. Educational Background

Additionally, I also compare the work time per week among three degrees: HS-grad, bachelor and master. (Fig. 3)

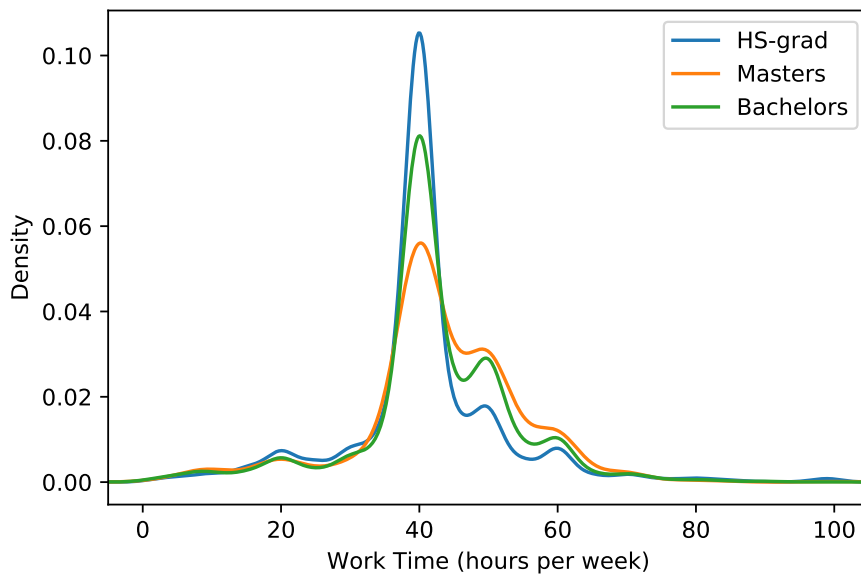


Figure 3: The work time per week among different degrees.

As is shown in Fig. 3, people with a higher degree tend to invest more time in their work, which probably due to the love for their work or enormous work pressure.

### 3.3.3 Job Catagories vs. Work Time

I am curious about the jobs that take people more than 50 hours a week. Therefore, I plot the distribution of such jobs as a pie figure (Fig. 4).

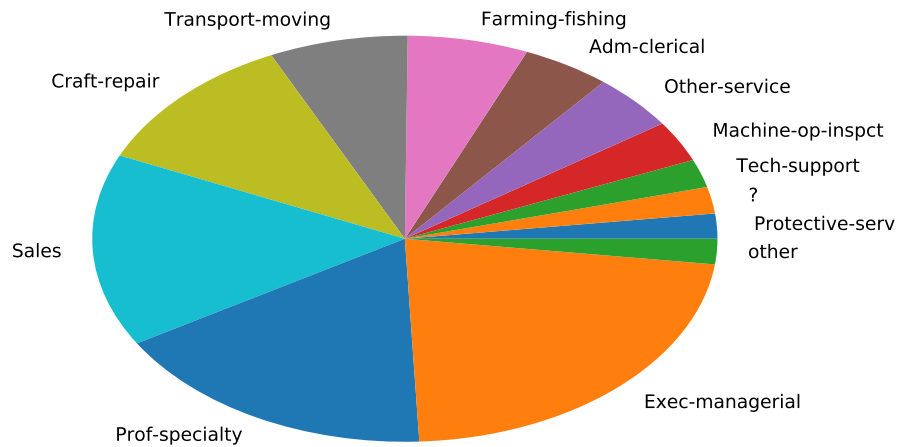


Figure 4: The jobs that take people more than 50 hours a week.

Different from my intuition, the result indicates that time-consuming jobs are focused on management and research fields, instead of manufacturing industry.

## 4 Conclusion and Discussion

In this project, I carry out the visualization and exploration of *Adult* dataset and discover some interesting phenomenons reflected from it.

According to the results of above analyses, the distribution of each attribute has some kinds of relation with others. Thus, I think I can train a model to decode this relation as some weights and predict target attributes from others in my future learning process.

Ultimately, I tend to express my sincere thanks to Professor Chaojun Lu for his patient explanation and guidance in lectures! Thank you!

## References

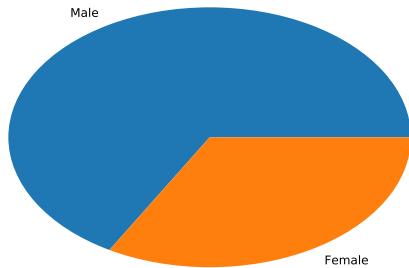
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- [8] “matplotlib.” <https://matplotlib.org/>.
- [9] “scikit-learn.” <http://scikit-learn.org/stable/>.

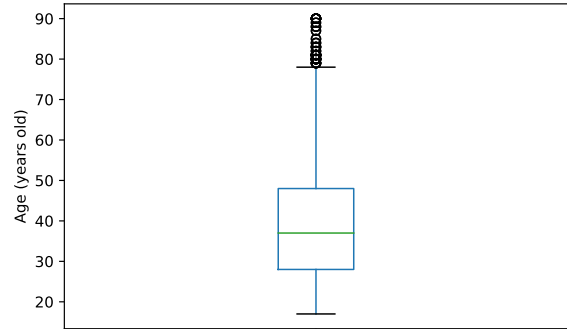
# Appendix

## A Distribution of Other Attributes

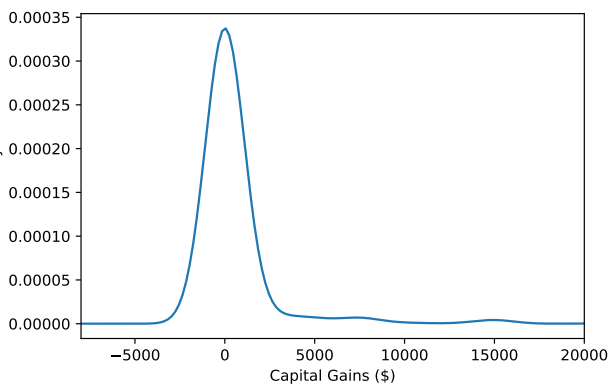
In this appendix part, I would show all distributions of other attributes in *Adult* dataset <sup>†</sup>.



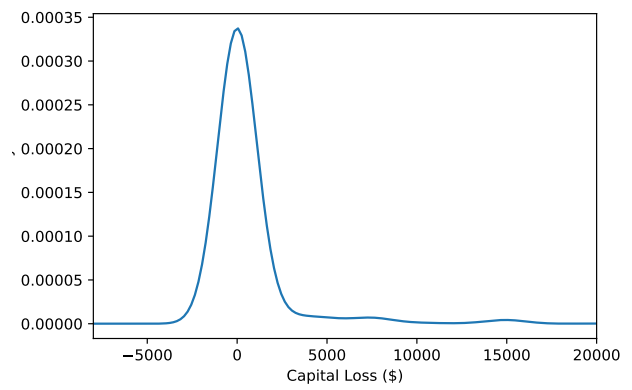
(a) Distribution of Gender



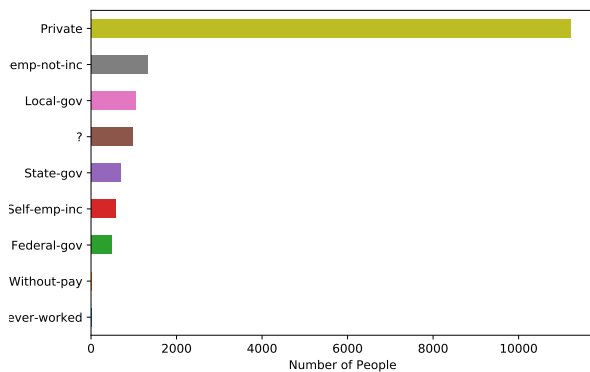
(b) Distribution of Age



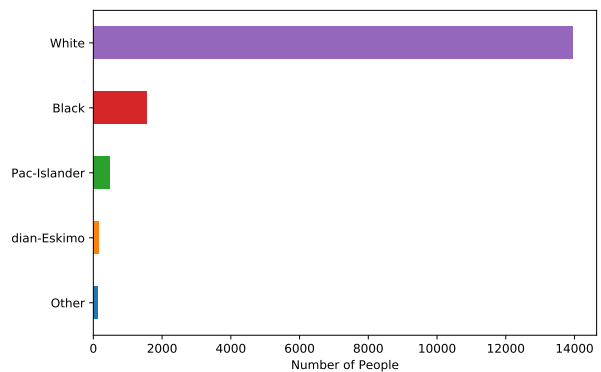
(c) Distribution of Capital Gains



(d) Distribution of Capital Loss



(e) Distribution of Work Categories



(f) Distribution of Race

Figure 5: Distribution of Other Attributes.

<sup>†</sup>Due to political problems, I am not going to plot country attribute.